Saturday Night or Fever?
Context Aware Music Playlists

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Abstract. Context awareness provides opportunities for enhanced user experience, interaction and customisation of electronic devices, particularly those which hold large data sets of information which may often only be relevant to a user in certain scenarios. In this work, we examine how context awareness can be applied to the automatic generation of music playlists on mobile music devices, such as MP3 players and mobile phones. We hypothesise that the type of music which a person might wish to listen to will often be influenced by external factors such as the time of day, the ambient temperature, amount of ambient or background noise, their current amount of physical activity, and their emotive state, to name a few.

We detail the results and data sets of preliminary investigation into several human movement scenarios, emotional status and external factors. These results are obtained by employing the cost-effective Wiimote controller to record acceleration profiles. The Wiimote is assessed against a professional level, high-cost, motion capture device to identify if such portable devices are useful in everyday scenarios. Base values for subject locomotion were investigated for the Wiimote device and verified and analysed using the Qualisys 3D-motion capture system. This was done for setting a base line for the subject forward velocity, but also to allow the research into further complex locomotion studies for this project. A model of the playlist generation system is provided, which can be used to simulate responses to various type of context-informing input.

It is noted that the system has been implemented using a fuzzy rule base system (FRBS). This will allow the initial construction based on a knowledge base relating a suggested emotional state (*E*-state) based on various inputs. The longer term concept is to investigate the adaptable nature of the initial knowledgebase and allow it to adapt to an individuals actual emotional state preferences. It is suggested that further research into the implementation of a Self-Learning Fuzzy Rule Based System (SL-FRBS).

1. Introduction

The generation of an automatic playlist is a useful resource for portable music players, especially given the storage capacities of currently available which are continually increasing. This means that the average listener with an MP3 or other digital music player will often have a database which has a membership of tens of thousands of songs, possibly even more! The factors which influence the choice of music a listener wants to listen to will be influences by many factors, but especially the user's current mood or emotional state, their current activity (if any), and the range of other external and environmental factors around the listener, such as the temperature, amount of background noise, time of day, etc. Rather than have a user cycle through such large databases to find music which they want to play, automatic playlist generation, in an ideal scenario, attempts to select and play music which it has determined the user would currently like to listen to.

Existing recommendation and playlist generation systems rely upon the ability to make correlations and measurements between songs in a music database in order to automatically generate or order the music in such a manner that the listener is automatically provided with music which (it is hoped) that they will like. To date, this has mainly been achieved by analysing the user's listening trends and habits as well as analysing the songs in the database to extract information about the musical content itself.

In this work we propose, and provide initial results of, the development of an automatic playlist generation system which not only implements these previous approaches identifying user *trends* and *content*, but also consider the current *context* of the listener and how this might influence their desired musical choices. A diagrammatic overview of the complete system we propose is given in Figure 1. Not only this, but in order to provide such a customised system, we propose that techniques of fuzzy logic and self-learning systems are suitable to efficiently carry out this task.

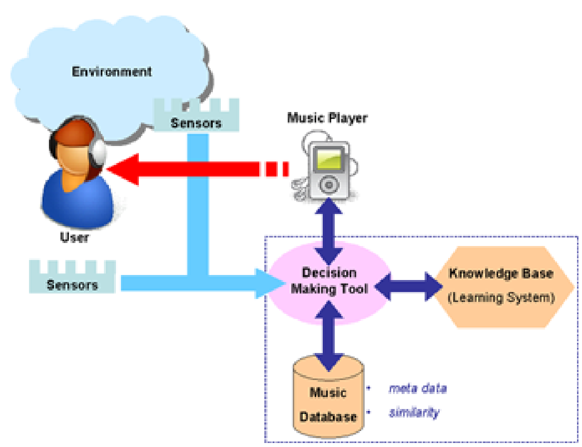

Figure 1: Context-Aware Playlist Generation

2. Related Work

Implementing automatic playlist generation is not a new field and has a long history relating to the organisation and recommendation of music tracks present on a music player. A detailed overview of alternative, historical approaches for automatic playlist generation is beyond the scope of this work, however, we briefly present an overview of the field and refer the reader to the references made in this section should he or she wish to gain a deeper knowledge of playlist generation techniques [1, 2, 3, 4, 5, 6, 7].

Initially, recommendation and playlist generation systems relied on abstract or meta-data level information and user preference in order to order the music tracks. These systems are not hugely different from Automated Collaborative Filters (ACFs) [8] in that they track and correlate user preference and build up table of similarity based on musical information such as artist and genre [1, 2, 3]. Although the can take simplistic forms by counting number of plays, favourite artists, etc. the processes of learning user preferences purely based on these factors can also take more complex forms [3].

More recent work has been focussed on extracting and analysing content present within the user's music collection and making decisions based upon similarity metrics or correlations, available as a result of content analysis. A more notable example of this type of analysis is in the field of audio thumbnails [4, 5, 6]. Such content information can then be coupled with the meta-data and user preferences mentioned previously in order to provide, what is generally agreed to be, a more suitable and effective system for playlist generation and music recommendation [4, 5].

In similar work to this paper, Reynolds *et al*. propose systems more advanced than the more conventional approaches to playlist generation mentioned earlier. Their work supports the theories that contextual information is also highly valuable and appropriate when suggesting or ordering musical tracks for the listener. In fact, they mull over many of the factors which we propose to be crucial in our own work, and explain in more detail later in this paper. Reynolds *et al.* consider variables such as temperature, activity and location to be incorporated as meta-data, and also indicate that the mood of the listener is another key variable which must be considered in automatic playlist generation. Their work also presents an excellent overview of the history of automatic playlist generation and the links between music and mood or emotion [7]. A detailed exploration of emotional states, measurement and music goes beyond the intended scope and context of this paper, however the reader is further referred to the work of Meyers who an in-depth exploration of the links between emotion and music [9].

We approach playlist generation from a similar set if initial hypotheses and notions of employing contextual knowledge. We see our work as a natural of extension from Reynolds *et al.* A limitation of their work was that there was only minimal identification of the practicalities and implementation present. In our work we begin to examine how to measure and put into practice context-aware playlist generation based on a number of bio-physical measurements.

3. Context

Mobile devices have become increasing computationally powerful and as well as functioning as digital music players, contain more and more peripheral devices such as cameras, touch screens and accelerometers. The Apple iPhone and iPod, in particular, is a high profile example of such a device, although there are other competing products available and in development. The power, connectivity options and range of data sources becoming available in mobile devices means that a range of mechanisms can be devised to allow the extraction of contextual information [10]. Principle contextual information initially of interest comes from two main sources: the user or listener and the environment in which the listener exists. This is further ratified by Reynolds *et al.* who also consider contextual input parameters from these two domains [7].

3.1. The Listener

Information which can be extracted from the user is arguably the most useful data which can be acquired if one wishes to determine contextual information regarding the listener's current emotional state and level of activity. This is illustrated in more detail in Figure 2 which is presented as a subset of the previous diagram in Figure 1.

The emotional state of the user is highly likely to influence the type of music which they wish to listen to. Listeners who are happy or contented are likely to desire their favourite music tracks and music which is from genres which is known to have positive effects on happiness and reflect and stimulate their current emotional state. Equally, a listener who is unhappy might wish to listen to slower, calmer music that fits with their current mood. However, this is not to negate the fact that a sad or unhappy listener might listen to upbeat, happy music in order to change their mood. Therefore, the listening requirements cannot be based purely upon determination of emotion, or at least, multiple inputs are needed to determine if a sad listener wishes to remain sad or wants to be cheered up. We propose that mechanisms such as skin conductivity and heart rate might be acquired directly from the user, before being sent to a decision making tool which also took into account other parameters and semantic knowledge of the music database.

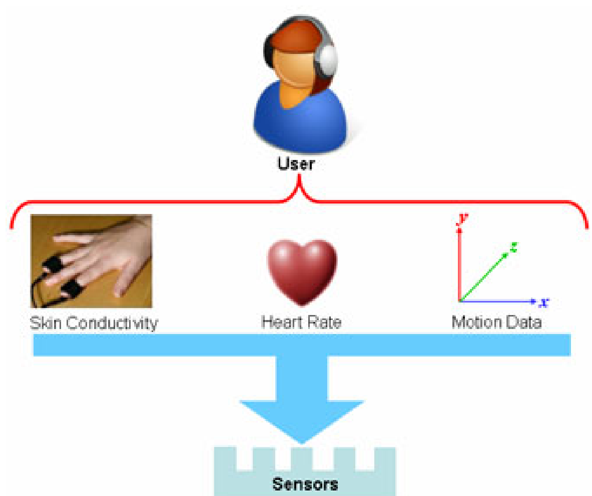

Figure 2: Sample Human Input Parameters

The other major factor interest at this stage is the amount of movement or physical activity the listener is engaged in. If the user is moving a lot then it is reasonable to suppose that they might be exercising or engaging in an focussed physical exertion, in which case they would be likely to desire music which reflects this physical motion and might feature strong, driving beats and tempos which are relatively high, greater than 120 beats-per-minute (BPM), for instance. An easily available, low cost device which is already on the market and can be used to detect three-dimensional (3D) motion is the Wiimote, illustrated in Figure 3, the remote control device designed for use with the Nintendo Wii games console. The Wiimote can be used independent of the Wii console to communicate with Bluetooth-enable devices, such as computers and provides valuable motion information via its accelerometers [11].

Figure 3: Nintendo Wiimote Controller

The ability of mobile devices to provide motion data is initially a very interesting concept when it comes to considering applications for these features, beyond those originally conceived for the device. This combined with the ability to attain other real-world and user information from sensors and direct input means that information regarding the user's current context can be described and learnt from observations of subjects using the devices.

3.2. The Environment

Factors in the environment around the user too, are likely to have an effect on many factors which influence the listener's habits and preferences when playing music. A number of parameters related to the physical environment as well as environmental metrics can provide suitable input to a decision-making system. Figure 4 provides illustration of how environmental inputs fit into the playlist generation system.

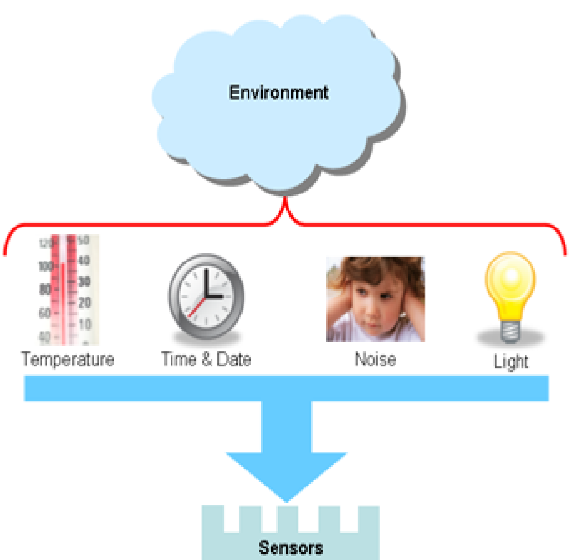

Figure 4: Sample Environmental Inputs

Consider firstly, physical phenomena around the listener, such as the ambient temperature, humidity, acoustic noise, and levels of light, for example. When high temperature and high humidity are present, we suggest that two scenarios are possible. The first may be that the user will be tired and at rest (determined via motion detection) in which case music of lower tempo and which provides a more relaxing experience may be required. However, an alternative may be that the user wants music to stimulate them perhaps because they are exercising or deriving a positive, happy feeling from the strong temperatures (such as when on the beach during a holiday). This can be further refined by measuring the amount of light. If light levels are low then it is most likely night time and, again, in combination with movement and ambient temperature the user might wish to either dance or relax and chill-out. The amount of ambient noise is useful firstly to help ensure that the listener is provided with a constant, desired volume level proportional to the amount of noise in the environment (within reason). It might also be used to determine if the user is inside or outside.

4. Initial Implementation & Results

To begin to assess the ability to gain contextual information from sensors and the usefulness of this information in deriving an emotional state (*E*-state) we implemented a small-scale system for playlist generation which would analyse a number of input factors and apply these in ordering a small music database consisting of eight songs, shown in Table 1.

Table 1: Music Database used in Testing

ID	Artist	Song
0	Daft Punk	*One More Time (Radio Edit)*
1	Fun Lovin' Criminals	*Love Unlimited*
2	Hot Chip	*Over and Over*
3	Metallica	*Harvester of Sorrow*
4	Pink Floyd	*Comfortably Numb*
5	Sugababes	*Push The Button*
6	The Prodigy	*Breathe*
7	ZZ Top	*Gimme All Your Lovin'*

4.1. Defining Input Parameters

Through some initial studies of the input parameters we are able to define and categorise a number of states against which any incoming data to the recommendation system can be matched in order to tag the current input state and make decisions based on this state attainment. This applies across all of the sensor input available to the recommendation system. It should be noted at this stage that the states currently defined are not necessarily absolute at this stage and are often indicative. These are easily refined and extra levels of granularity or simplicity can be easily introduced by adjusting the size of the membership sets and/or adjusting the state value thresholds.

Initially we define four locomotive states, which can be extracted from the Wii controller or another similar device such as the motion data from an iPhone/iPod or from a higher level source such as the Qualisys motion capture system. These four possible states and their associated values are defined in Table 2. These values are attained from input directly attained from the user of the system using such a device.

Table 2: Locomotive States

Standing	Walking	Jogging	Running
0 m/s	1.1 m/s	2,2 m/s	3,5m/s

Similarly, we must define some standard states and ranges for any other parameters which we intend to implement at this stage. Due to limitations of equipment availability and time, we decided to focus on additional inputs from the environment at this stage, rather than other factors directly read from the listener or user. Therefore, we define states and parameters for a number of environmental factors, which are presented in Tables 3 to 5.

Table 3: Temperature States

Cold	Warm	Hot
15-18 ^{o}C	20-23 ^{o}C	27-30 ^{o}C

Table 4: Lighting States

Dark	Grey	Day Light	Light	Sunny
0-3	2-4	3-5	4-7	6-10

Table 5: Weather Condition States

Heavy Rain	Light Rain	Drizzle	Dry
0-2	2-5	4-6	5-10

At this stage, the parameters are loosely defined from empirical and historical knowledge of the individual and are not yet finely tuned for the playlist generation system. In order to make the input functions more realistic, usable and suitable to the listener, they must first be fuzzified.

4.2. Fuzzy Logic Model

To make a decision on the emotional state of the user, based upon the input data sets, we employ a fuzzy logic system, specifically a Fuzzy Rule Based System (FRBS). Fuzzy set theory is proposed by Zadeh [12]. The concept of fuzzy logic is the ability to formalise approximate reasoning. An application of this theory is FRBS which utilises the concept of fuzzy rules. Such systems comprise of two main features: An inference engine and knowledge base. Figure 5 shows an illustration of a generic FRBS system. Mamdani and Takagi-Sugeno-Kang (TSK) FRBS were considered in this study, with the later TSK being implemented as the main FRBS in this paper. Our initial test FRBS is implemented using the Matlab FIS environment. The Matlab Fuzzy Logic toolbox provides a useful tool for the initial realisation of the fuzzy model.

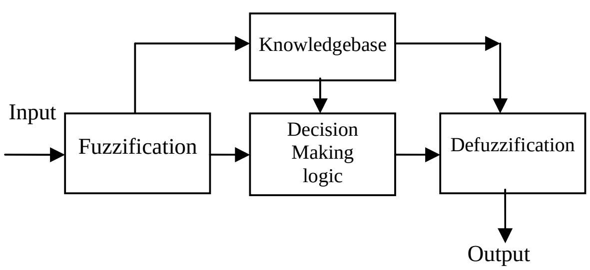

Figure 5: Schematic of FRBS

A fuzzy set L defined on a Universe of discourse U may be characterised by a membership function $\mu_L(x)$ and is defined over the interval [0, 1]. For this case the range is based on measurements taken for a single subject. The following figures define how the input parameters are configured in the fuzzy logic model.

The definition of membership of locomotive states is shown in Figure 8 and was obtained by empirical observations and experimentation with motion detection using both the Wiimote and a Qualisys system to capture motion. The Wiimote controller was selected for this study due to its suitability to provide hands-free and low cost motion feedback to the FRBS. The Wii controller provides acceleration feedback for the three the x, y and z axis. Initial usage of the device is to obtain an approximate value for the forward linear velocity V from the acceleration Δ_a across a period of time Δ_t as

$$V = \Delta_a \Delta_t . \quad (1)$$

We experimented with extracting locomotion data from the Wiimote controller and compared this to the data which can be extracted from a full-blown motion capture system; the Qualisys. Figure 6 shows how placement of the Wiimote on subjects was achieved and Figure 7 provides an image of a subject being tracked by the Qualisys system.

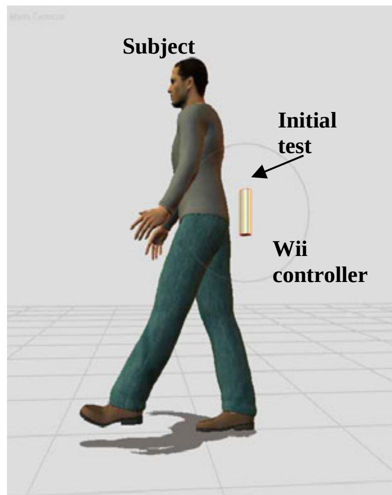

Figure 6: Locomotion Extraction with Wiimote

Figure 7: Motion Capture with Qualisys

As can be seen, the Qualisys system is more cumbersome than the Wiimote and actually requires a number of cameras to track motion accross a very fine range. However, the Wiimote is much less intrusive and can be attached to a belt or put in a pocket. Furthermore, provided the Wiimote sunject remains within the transmission radius of the Bluetooth transceiver (either 10 meters or 100 meters in laboratory conditions), the user will have complete freedom of movement. This makes the Wiimote not only better for recording natural movement, but much more practical for deployment into real-world scenarios, such as playlist generation.

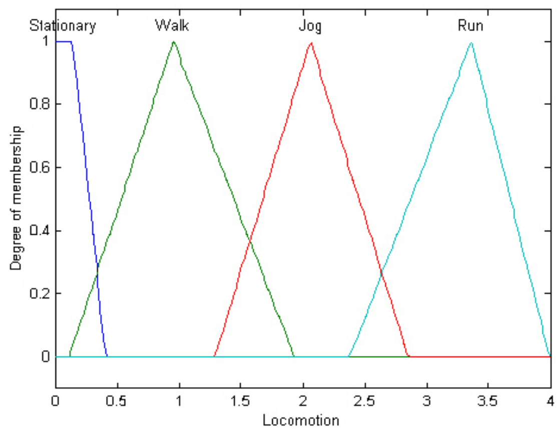

Figure 8: Fuzzy Locomotion Set

Ambient temperature is illustrated in Figure 9 and membership criteria were gained by measuring a range of location conditions and consulting average temperature conditions in the UK. It is expected that for implementation in other countries, this kind of contextual information is subjective and would be defined at initialisation.

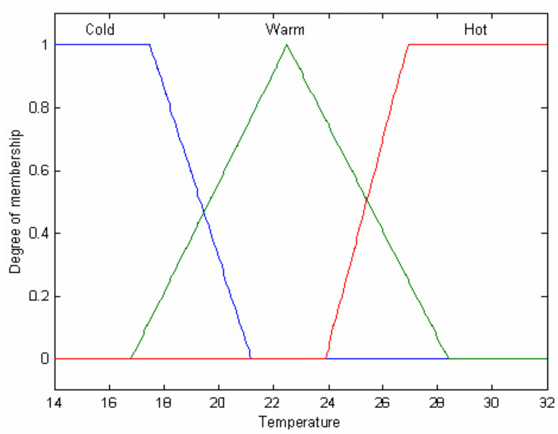

Figure 9: Temperature Set

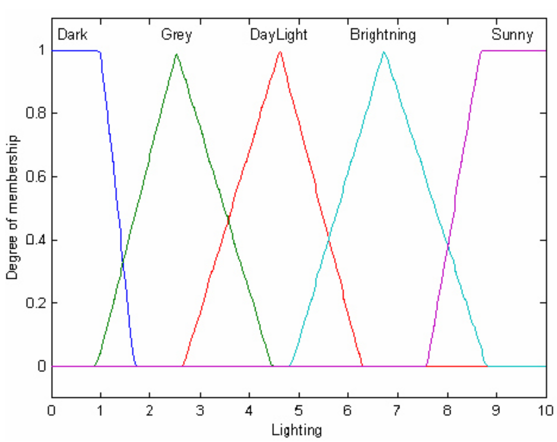

Figure 10: Lighting Set

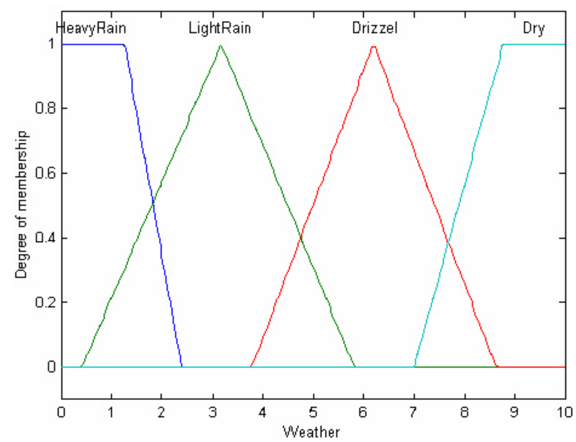

Figure 11: Weather Conditions Set

The set of lighting condition classification is shown in Figure 10 and possible weather conditions set is in Figure 11. Again, membership criteria are based upon empirical observations.

These factors are combined as inputs to the FRBS system to allow an output of emotional state estimation as can be seen in Figure 12.

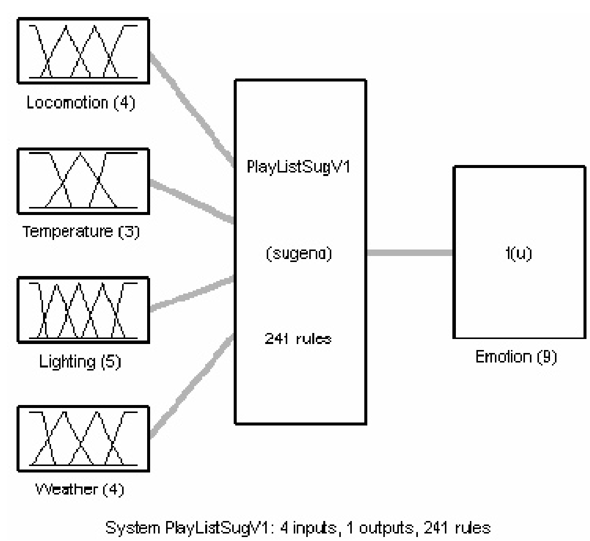

Figure 12: Suggested TSK-type FRBS

The current rule base has been derived on the expert or suggested emotional state of a subject for various states of inputs. Input ranges for locomotion and temperature have been determined experimentally, while Lighting and weather are base on a incremental scheme and a initial triangular or trapezium membership function was chosen initially and further research on the rule base and fuzzy set distribution, membership functions will provide refinement of the system performance.

4.3. Defining Output of Emotional State

Currently a single output state is generated from the fuzzy logic model which is used to indicate the predicted emotional state of the user based upon the input parameters. We define a set of 10 emotional states or outcomes which are broadly defined as having membership of 5 categories. This can be seen in Table 6 and a schematic of the integration of output states is shown in Figure 13.

Table 6: Emotional States

Depressed	Unhappy	Neutral	Happy	Zoned
0-3	3-4	4-6	5-8	7-9

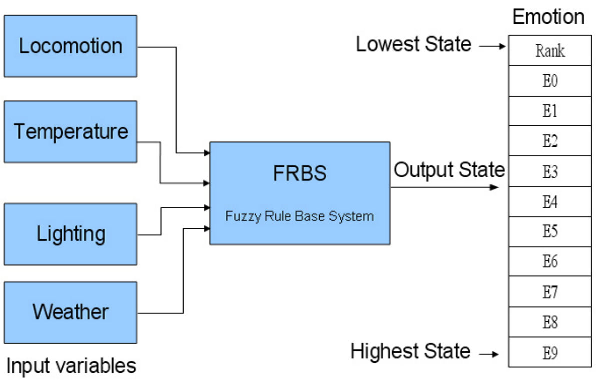

Figure 13: PlayList Organising Tool (PLOT)

5. Initial Results

5.1. The Wiimote as a Motion Device

The Qualisys motion capture system allowed comparative data capture of the three Primary directions of subject motion. For this paper we are primarily interested in forward velocity. It is noted from the Qualisys results a potential coupling is possible due to placement of the Qualisys Sensor. The data recordings from the Wiimote and the Qualisys system were conducted under the same conditions in order to fully investigate the comparative effectiveness of each device.

Results measuring motion using the Qualisys are provided in Figure 15 for walking, jogging and running states. The graphs from the Qualisys plot forward motion, over a fixed distance, across time for each of the three tests. The fixed distance is covered over increasingly short times as the subject increases speed from walking, jogging and running. Interpretation of time comes from multiplying the number of samples by the fixed sampling rate on the Qualisys used for each test.

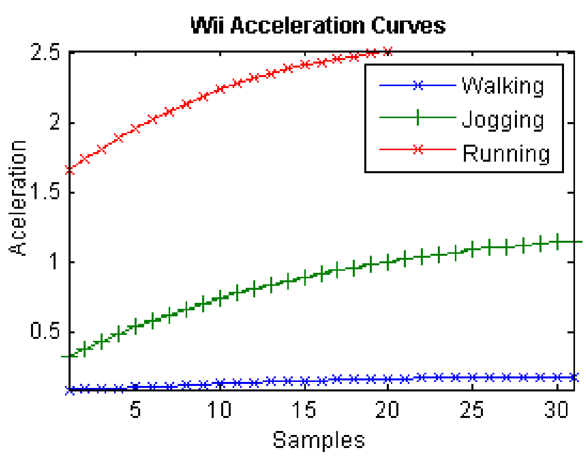

Figure 14: Wii Acceleration Curves for Motion

Comparative data from the Wiimote is presented in Figure 14 and also demonstrates locomotive state can be simply established by correct interpretation of the accelerometer data over a fixed-rate sampling period of 10Hz. The illustrations from the Wiimote present the velocity of the user over samples (time). As can be seen from the illustration, the states of walking, jogging and running are clearly identifiable.

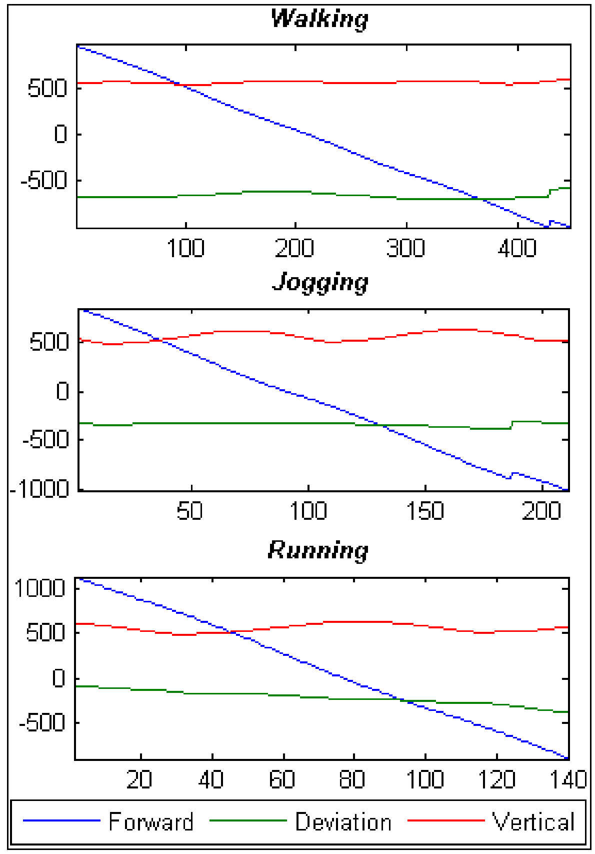

Figure 15: Motion Data from Qualisys

5.2. Fuzzy Playlist Generation

We configured the system with a number of expert-informed parameters which related emotional state to a sample collection of input parameters such as locomotion and environmental factors. We carried these tests out over a number of subjects and established the knowledge in the fuzzy system using the average of these tests. The scenario configurations used are given below in code along with a textual description of the scenario and the average set of results relating to emotional state is presented in Figure 16. Although an average response is employed, there were strong correlations between the majority of the subjects and their perceived emotional state indicators, which indicate that the data recorded is reliable for those circumstances.

```
%1 Walking, temperature is hot, lighting is dark/grey and weather is light rain.
ip1=[1.5;28;2;2.5]
E(1)=evalfis(ip1, a)

%2 Stationary, temperature is cold, lighting is dark and weather is raining.
ip2=[0.1;14;1;0.5]
E(2)=evalfis(ip2, a)

%3 Stationary, temperature is Warmish, lighting is brightening and weather is dry.
ip3=[0.1;21;9;9]
E(3)=evalfis(ip3, a)
```

```
%4 Running, temperature is hot, lighting is
Daylight/Getting brighter and dry.
ip4=[3.5;30;5;9.5]
E(4)=evalfis(ip4, a)

%5 Walking, temperature is getting hot,
lighting is dark and weather is drizzling.
ip5=[1.5;16;1;6]
E(5)=evalfis(ip5, a)

%6 Stationary, temperature is hot, lighting
is grey and weather is dry.
ip6=[1.4;32;2.5;9.5]
E(6)=evalfis(ip6, a)

%7 Walking/Jogging, temperature is mild,
Daylight and it's dry.
ip7=[2;17;4.5;9]
E(7)=evalfis(ip7, a)

Emotions=floor(E*100)
```

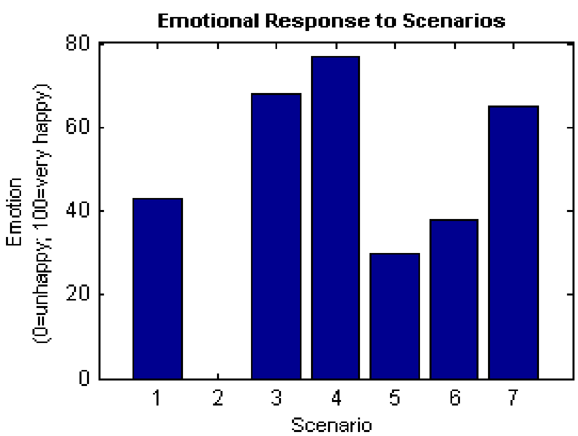

Figure 16: Results of Emotion Scenario Indicator Testing

Additionally, we constructed attached an emotional state range to each of the songs in our small database to which the output emotional state can be correlated. Table 7 shows the E-state range which, through pilot testing, we attached to each song.

Table 7: Song Database with *E*-States

ID	Song	*E*-state	*E*-State Median
0	*One More Time (Radio Edit)*	5-8	6.5
1	*Love Unlimited*	4-6	5
2	*Over and Over*	7-9	8
3	*Harvester of Sorrow*	0-3	2
4	*Comfortably Numb*	3-4	3.5
5	*Push The Button*	7-9	8
6	*Breathe*	0-3	1.5
7	*Gimme All Your Lovin'*	5-8	6.5

Table 8 shows the results of each of the seven experimental scenarios presented along with the resulting playlist to be generated. The grade in the playlist G is determined by taking a simple Euclidean distance measurement of the form

$$G(p,q)=\sqrt{(p-q)^2} \qquad (2)$$

from the song E-state median and the current E-state of the listener, based on the scenario. The playlist is shown as a ranked set of song ID numbers from the database for each E-state.

Table 8: Playlist Order for Test Scenarios

Scenario	E-state	Playlist order
1	4.3	1; 4; 0; 7; 3; 6; 2; 5
2	0	6; 3; 4; 1; 0; 7; 2; 5
3	6.8	0; 7; 2; 5; 1; 4; 3; 6
4	7.7	2; 5; 0; 7; 1; 4; 3; 6
5	3	4; 3; 6; 1; 0; 7; 2; 5
6	3.8	4; 1; 3; 6; 0; 7; 2; 5
7	6.5	0; 7; 1; 2; 5; 4; 3; 6

6. Conclusions & Future Work

We have demonstrated that the Wiimote can function as a highly useful instrument for measuring forms of human motion and in future plan to assess the functionality of other low cost motion devices such as the accelerometers which have been integrated into mobile music players such as the iPhone and iPod Touch. These devices, and the Wiimote functionality, can be further ratified by more comparisons with data extracted using high-end motion capture hardware, such as the Qualisys, mentioned earlier.

In terms of being able to attain a more reliable, and possibly multiple-faceted, emotional state indicator would be to develop a self-learning algorithm to provide an adaptive context list generation. This is something which we intend to pursue in the near future as it will provide a much more customised interpretation of the user's emotional states and musical preferences. Given that emotion is such a personal and almost unique experience for each individual, this is high in the list of priorities for future developments. The current system operation is to obtain an estimate for the emotional state of the subject and to use this as a factor for the subjects play list organisation. The list update is based on a predetermined time up-date interval. The current E-state is used to modify the play list. We have used a single output value based on a Multiple Input Single Output (MISO) model. Further research based on Multiple Input Multiple Output (MIMO) would allow multiple meta-data selection process based on beat or tempo of the music file, for example.

The initial FRBS has been implemented and provides a baseline model for the development of a more defined model. Fuzzy sets and memberships functions need to be refined to allow further optimisation of the system, extending the range of inputs to allow a far more flexible system. Of interest is the modification of the suggested rule base. An aspect is the ability to modify the initial rule base with rules more selective of the subjects' individual emotional states. Approaches being investigated based on a self-learning strategy:

1. Modifying the fuzzy set definitions. Modification of the fuzzy sets implies potential issues with the fundamental nature of the linguistic meaning. Mamdani suggested that a change in the fuzzy set definitions should be avoided although potential minor or small modifications may be possible [13].

2. Modifying the set of rules in the rule base. Given a fuzzy relation is used to describe each rule in the rule-base of the FRBS. Then given the general rule expression:

R_n : If m is M_n AND t is T_n AND l is L_n AND w is W_n THEN u is U_n

Where
R_n = the fuzzy relation of rule n.
$M, T, L, W,$ and U are linguistic labels assigned to each variable of rule n.

The general relation 'R' is constructed as the union of individual relations

$$R = \bigcup_{i=1}^{n} R_i \ . \qquad (3)$$

So that using Zadeh's compositional rule of inference Zadeh the output fuzzy set assuming for this case a Mamdani model then

$$u^o = (m^o \times t^o \times l^o \times w^o) oR \ . \qquad (4)$$

It is therefore feasible to modify the rule-base based on factors such as the individual's emotional preference, or additional inputs such as heart rate. The system would then potentially provide an emotional state ranking that is more reflective of that individual.

Another point for development is to attach a number of *E*-states to each song in the database, since certain types of music may be suitable for two or more *E*-states. Through further investigation, we propose to develop a primary emotional rating and then a secondary and possibly third *E*-state. Furthermore, the *E*-state suitable for each song can be investigated until a much deeper, accurate estimation of the range of suitable *E*-states can be determined.

The system presented at this stage is more limited than the outlined system presented in section 1 of this paper. As mentioned, this was due to equipment and time constraints, therefore future work would include employing further sensor systems as inputs to the playlist generation system particularly those which are concerned with input from the listener, rather than the environment. It can be argued that inputs from the environment are factors which, we *predict* are likely to *influence* the listener's emotional state. However, to derive measurements and indicators *directly* from the listener suggest a much more robust and reliable *evaluation* of the emotional state.

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